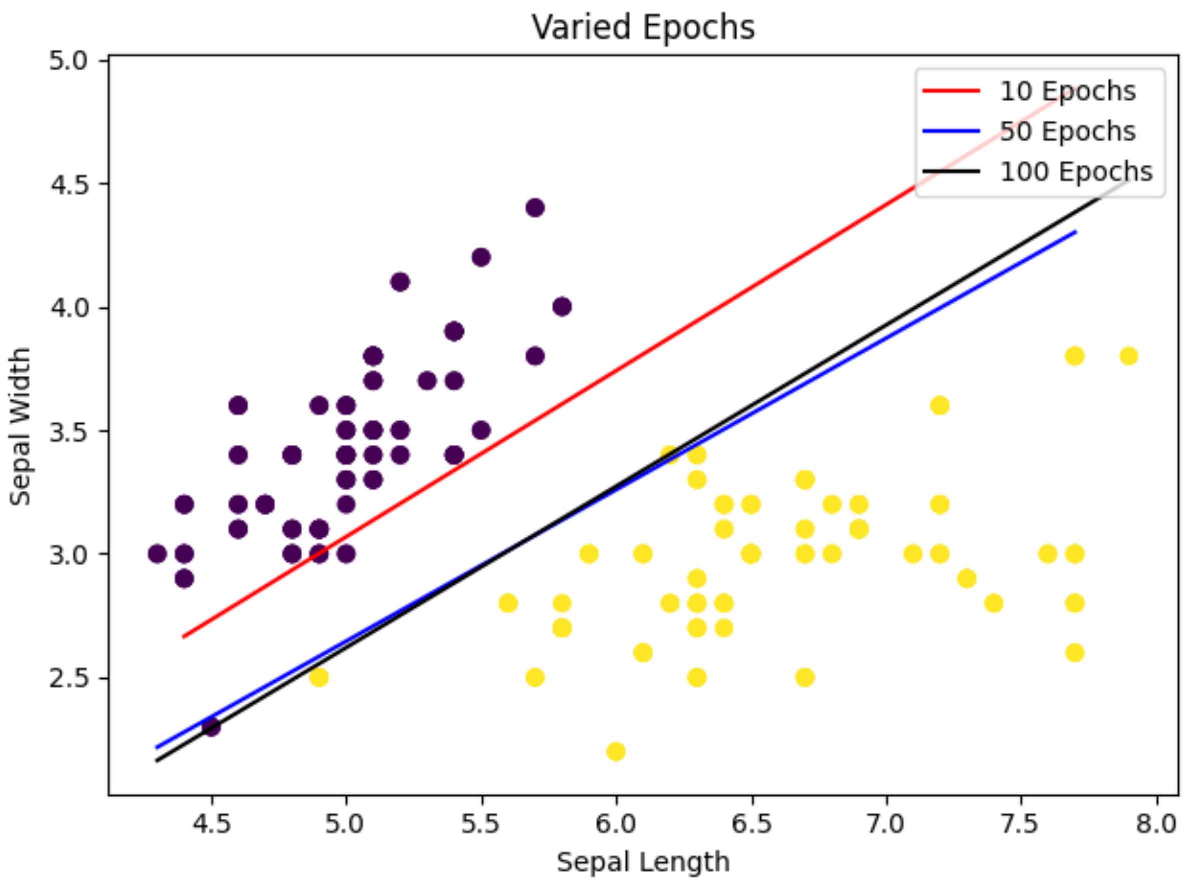
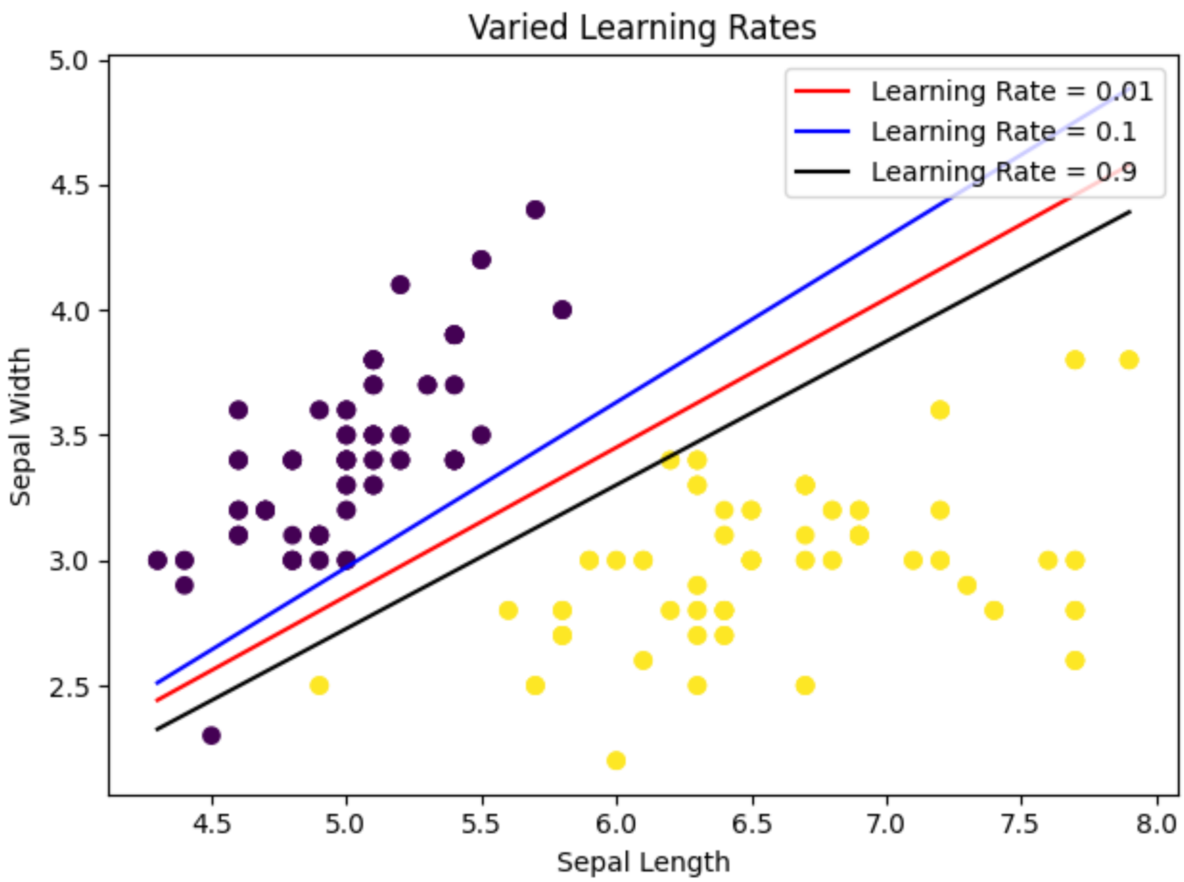
HW 2 Report

(1) Varied Epochs



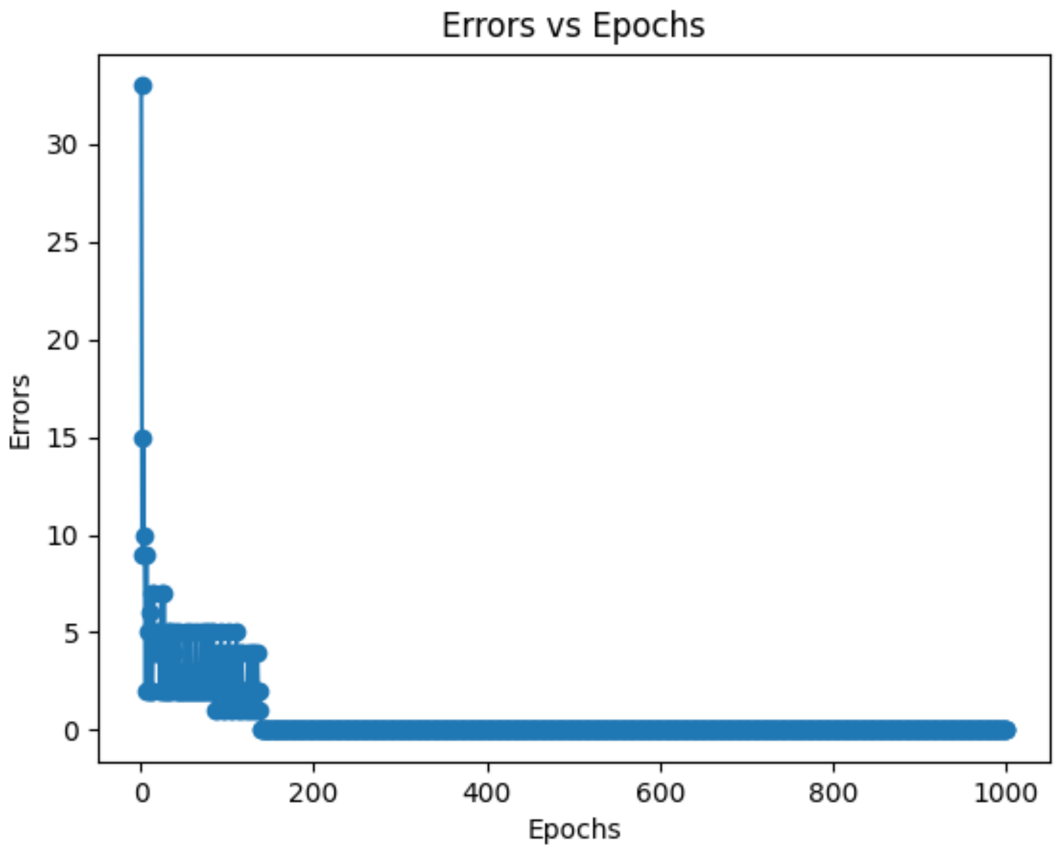
By keeping the learning factor constant and varying the number of epochs, we can see the effect that additional training has on convergence. As the number of epochs increases, the algorithm has more opportunities to fine tune the bias and weights which generally leads to a more accurate decision boundary. We can see in the graph that as the epochs are increased from 10 to 100, the boundary begins to stabilize and classification improves.

(2) Varied Learning Factors



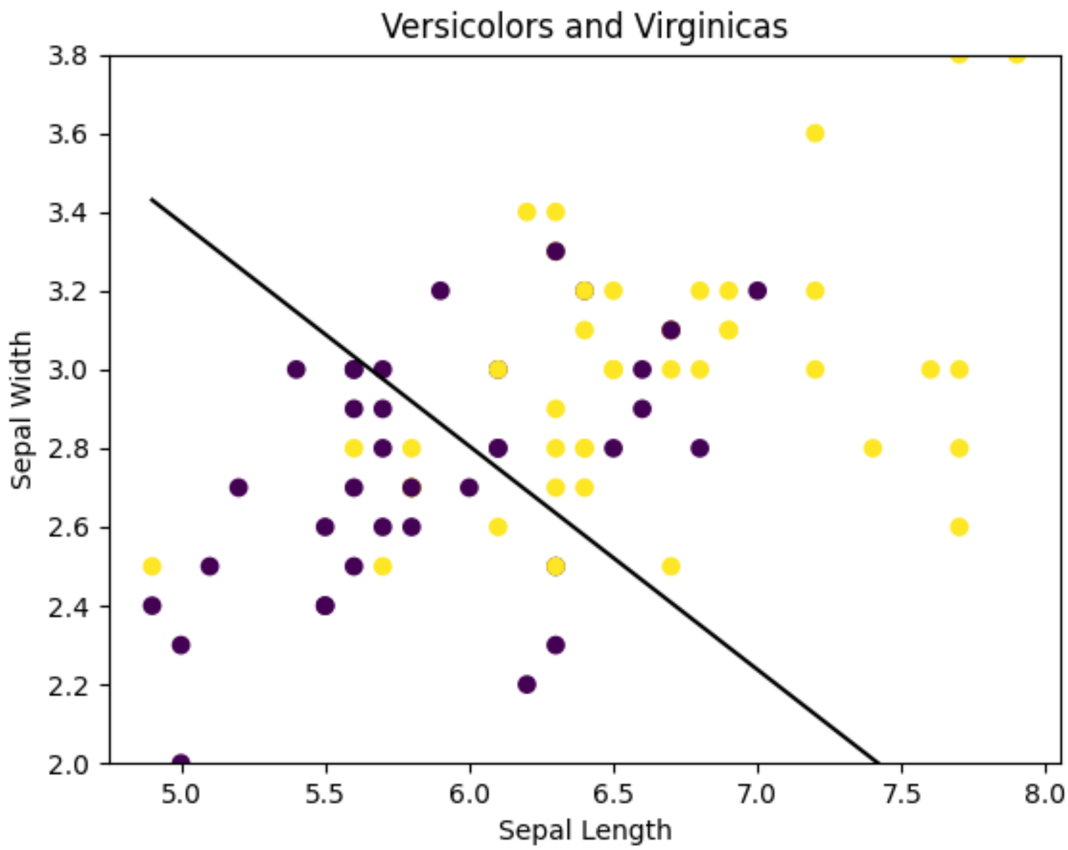
Keeping the epochs constant and varying the learning factor shows the effect that different learning rates have on the decision boundary. The Perceptron algorithm determines a boundary by oscillating over an acceptable solution, and the learning factor controls the rate at which this happens. This means that a high learning factor may cause drastic jumps in the boundary and in general will converge on a solution faster. Smaller learning rates will take much longer to converge on a satisfiable boundary and may require more epochs.

Errors vs Epochs



As the number of epochs increase, the number of errors approaches zero. This demonstrates Perceptron is converging on a boundary that will lead to correct classification. However, if the data is not linearly separable, the errors may never reach zero as the algorithm cannot achieve a boundary that perfectly separates the classes.

(3) Versicolor



When using sepal length and width to classify Versicolors and Virginicas, the algorithm fails to accurately classify samples. This is because the classes are not linearly separable. We can see this represented in the graph as there is no possible way to draw a straight line that separates the two sets. To use Perceptron to distinguish between Versicolors and Virginicas, we would need to use other features that draw clear distinctions between the classes.